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Mental Stress Evaluation using an Adaptive Model

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***Abstract*—-Chronic stress can have serious physiological and psychological impact on an individual's health. Wearable sensor systems can enable physicians to monitor physiological variables and observe the impact of stress over long periods of time. To correlate an individual's physiological measures with their perception of psychological stress, it is essential that the stress monitoring system accounts for individual differences in self-reporting. Self-reporting of stress is highly subjective as it is dependent on an individual's perception of stress and thus prone to errors. In addition, subjects can tailor their answers to present their behavior more favorably. In this paper we present an adaptive model which allows recorded stress scores and physiological variables to be tuned to remove biases in self-reported scores. The model takes an individual's physiological and psychological responses into account and adapts to the user's variations. Using our adaptive model, physiological data is mapped efficiently to perceived stress levels with 90% accuracy.**

***Index Terms*—Stress, HRV, EDA, Wireless Sensors, Self-Reporting Score, SVM**

I. Introduction

Stress is ever prevalent in modern society. The impact of long term stress can not only be physiological but also psychological. Chronic or long term stress may cause or trigger diseases such as hypertension, insomnia, diabetes, asthma and depression [1] and may also lead to social problems such as marriage breakups, family fights, road rage, suicide and violence [2]. To accurately diagnose chronic stress, physicians need to monitor and report overall personal state for several months. As stress is a psychological reaction to external inputs and demands that exceed the built in capacity of the human body [3], personal state monitoring includes not only monitoring the physiological reactions to stress but also the perceived psychological impacts of the stressors. Assessment of the physiological impact can be achieved with minimally-invasive wearable sensors that monitor measures such as heart rate variability, respiratory rate and skin conductance [4]. The psychological impact is more difficult to ascertain and requires wearable sensors to monitor daily stress levels in a person's routine day-to-day life.

Due to individual variability among subjects, the physiological impact of stress is different on each individual. The physiological responses occur due to hormones from the brain and pituitary glands, whose level is highly dependent on an individual's psychological state and their perception of the situation faced [5] thus varying their severity or scale of stress.

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Accurate metrics of stress thus need to incorporate assessments of the individual's psychological state along with various physiological changes inside the human body. This complicates the design of a universal protocol for measurement of stress as subjective adjustments are necessary to incorporate an individual's conditions.

An accurate stress monitoring system thus needs to assess both the physiological and psychological impact of stress on an individual and translate these assessments into an accurate quantitative metric that is of value to physicians. This quantitative metric should be able to correlate the individual's perceived psychological stress indices with their physiological measures. In this context, we have developed a generalized adaptive model that enables extracted physiological measures to be adapted to correspond to the user's perceived psychological stress levels. The adapted scores are then used in a pattern classification algorithm as 'ground-truth' stress levels to be predicted from wearable sensor signals. The result is thus an accurate estimate of the level of stress experienced by the subject based on both their physiological and psychological responses.

In section II, we discuss the self-reporting techniques used to determine the psychological impacts of stress and the need for an adaptive model to reduce errors introduced in stress assessments due to subjective personal judgments. In section III, we present the methodology adopted to collect data used in the development of the adaptive model. The design and implementation details of the adaptive model are provided in section IV. In section V, advantages of adaptive model over a simple classification model are presented. A discussion of results, conclusions from this study and future directions are presented in section VI and section VII.

II. Self-Reporting Of Stress

The intensity of an individual's reaction to stress is relative to their ability to cope with danger in the given situation [6]. The same situation can give rise to different psychological effects in different people. The degree of stress recorded by the individual depends on their degree of control over emotions and their specific reaction [7]. For example people with higher levels of self-esteem are less likely to be stressed than those with lower self-esteem. To interpret a subject's perception of the level of severity of stress, self-reporting questionnaires are used. Self-reporting scores (SRS) are a set of scales, used to measure the conventionally defined negative or positive emotional states that represent anxiety and stress [8]. These scores were developed to identify individuals who meet essential criteria for a specific level of stress

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and anxiety.

However, there is a need to validate the accuracy and efficiency of the self-reported scores as the importance of scores is significant for stress related symptoms (self-reported scores provide opportunities for early intervention of people at risk).

A number of studies have used self-reported scores to link stress to physiological parameters. The depression anxiety scale was used on three samples of student population and it was found that somatic depression items such as sleep disturbance, constipation and fatigue represent the chronic stress more effectively than non-somatic depression items [9]. Cortisol levels and depressive symptomatology have also been directly correlated to negative mood and clinical depression [10]. Stress levels in 36 non-smoking medical students were examined using self-reported scores [11]. Spectral analysis of the heart rate variability (HRV) found a positive correlation between the low frequency (LF) power and stress scores. In another study [12] on two groups of women, one consisting of 36 single women with stress-related fatigue and a second group of 19 healthy females, it was found that the stress group has lower HRV values, higher temperature and lower O_2 saturation at the surface of the finger than the healthy group. Long term variations in HRV have been related to chronic mental stress in low and high stress groups as classified by their stress response inventory (SRI) scores [13]. Statistical testing was performed on a number of subjects to explore the validity of the perceived stress scale questionnaire (PSQ) with respect to a transactional model for stress [14]. It was concluded that highly perceived stress is directly proportional to work overload and work discontent.

Though self-reporting scores are beneficial due to their low cost, efficient analysis and ability to collect larger amounts of data, concerns have been expressed about the reliability of the extracted self-report measures [15]. Their robustness and accuracy can be disputed as self-reports are always more open to socially desirable responses than unobtrusive observations [16]. Generally, there are two types of socially desirable responses, impression management and self-description. Impression management refers to the deliberate tendency to give favorable comments to others and therefore is a form of deception and falsification. Self-description can be defined as a positively biased but it is subjective and depends on various factors. In this way, a respondent scoring high on self-description actually believes that his/her positive self-descriptions are true. Subjects tend to report what reflects positively on their own abilities. In general, it has been recommended that impression management and self-description scores should be thoroughly checked and verified by alternate methods such as performing objective analysis of the data [17].

To test the validity of self-reported scores, we have designed and developed an adaptive model that minimizes these deviations in stress scores. An individual's self-reported score is based on his physiological state and his perception of the situation. In a negative psychological mood or due to wrong perceptional judgment, an error or deviation is introduced in his score. Our adaptive model not only computes deviations in self-reported scores but provides tuning which incorporates into the system an individual's physiological variations and adjusts them accordingly to provide a generalized solution for determining their level of mental stress.

III. Methods

A. Hardware Details

Wearable sensors used for long term monitoring need to be not only comfortable but also accurate, so some markers such as blood pressure and blood volume flow are unsuitable [18]. Inter-heartbeat intervals (heart rate variability) are used as reliable measures for the determination of stress as with increased stress the heart rate variability decreases. Electrodermal activity (EDA) is also widely used for the measurement of stress. It is directly proportional to stress levels as with increase in stress, the EDA increases due to increase in conductivity of the body with sweating and perspiration [19]. Respiratory signals also provide a suitable measure of stress. During stress, respiratory rate increases and breathing patterns become irregular [20]. Of all the possible measures, HRV, respiration rate and EDA have been shown to be the most feasible for use in long term stress monitoring and as they can be measured wirelessly during the activities of daily living. A wearable sensor platform using these sensors can balance information content of the sensors with overall comfort and long-term wearability.

It is in this context that we developed a body sensor network to wirelessly monitor heart rate, respiratory rate and electrodermal activity, details of the system are described in [21]. To measure heart rate variability, the system uses a heart rate monitor from Polar Electro Inc. For respiration, a SA9311M respiration sensor (Thought Technology Ltd.) is integrated into the HRM strap. Electrodermal (EDA) activity is measured with two AgCl electrodes (Vivometrics Systems Corp.) on the index and middle fingers. The sensor network transmits data to a holster unit that contains a data processing unit, a sensor hub and a lithium-polymer battery where the data is stored onto a micro SD flash memory.

B. Experimental Activities

There were 22 students (age bracket: 18-30, male:12, female:10) who participated in the stress related experiments and Institutional Review Board (IRB under contract number: ER-99-186) approved the study. To develop an accurate metric that combines the physiological and psychological impact of stress in an individual, we collected data using our wireless wearable platform, while subjects performed a series of mental challenges, chosen to measure a range of stress responses in recorded physiological signals. To compute stress levels, the subjects were also asked to complete three surveys: stress and difficulty surveys following completion of each challenge and a post stress survey, immediately after completion of all activities. In these surveys, subjects were asked to self-score

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each activity on a 7-point Likert scale (1 corresponds to relaxing conditions and 7 corresponds to highly stressful situations). At the start of the experiments, subjects were asked to perform a 3-min deep breathing exercise (0.1 Hz breathing rate) to help bring them to a relaxed state. Deep breathing was also used between stressful activities to aid in recovery. The stress challenges consisted of a dual tracking task (subjects had to track a moving target in a computer screen using the mouse whenever a target letter appeared on the screen), memory search (subjects had to memorize a set of words and then identify them among various confounders), mirror tracing (on a paper printout, a pattern had to be traced manually which was visible only through a mirror), Stroop test (after being shown one of four words displayed in different ink colors, subjects had to click on one of four buttons according to the ink color), supine and tilt (subjects took supine and tilted positions) and public speaking (subjects had to deliver a public speech of 4 minute duration). Figure 1 below gives the sequence of activities in the experiment.

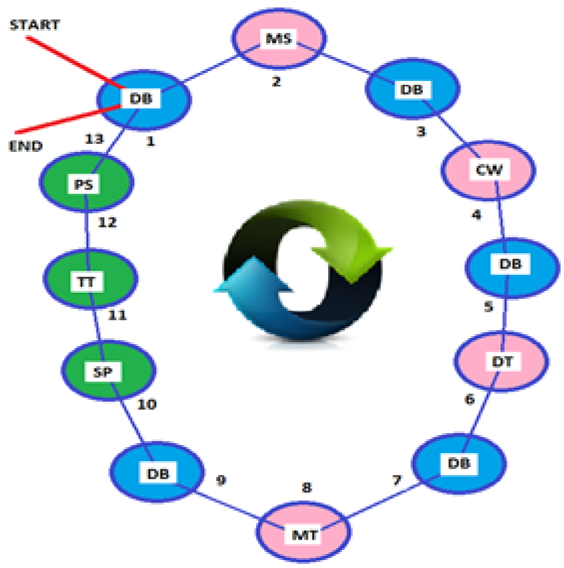

Figure 1. Block diagram of Activities, Deep Breathing (DB), Memory Search (MS), Color Word (CW), Dual Task (DT), Mirror Trace (MT), Supine (SP), Tilt (TT) and Public Speech (PS) represent mental challenges

IV. Adaptive Model

To provide medical practitioners with an accurate assessment of the personal state of an individual, we have developed an adaptive model that compares recorded physiological measures with self-reported scores to identify deviations in either of these two categories. Deviations identified in the physiological measures are adapted using a weighting factor scheme based on the median value of the features obtained from all the subjects. Deviations computed in the self-reported scores are used to identify unreliable rankings made by the subjects, which are then excluded from the data set. By identifying these deviations, the adaptive model provides a data set which more accurately reflects the subjects' physiological state enabling a reliable estimate of their stress levels.

A. Feature Extraction

During the experiments outlined in Figure 1, we measured electrodermal activity (EDA), heart rate variability (HRV) and respiratory rate while subjects performed the specified activities. The skin conductance level (SCL) and skin conductance responses (SCR) in EDA were computed using a regularized least-squares detrending method [22]. In this approach, aperiodic trend corresponds to the SCL and the residual denotes SCR. Two features, mean and standard deviation, are computed from SCL as follows,

$$\mu_{SL} = \frac{1}{N} \sum_{i=1}^{N} R_{SL}(t-i) \qquad (1)$$

where μ_{SL} is the average SCL trend for N samples of signature R_{SL}.
The standard deviation is computed as follows,

$$\sigma_{SL} = [\frac{1}{N} \sum_{i=1}^{N} R_{SL}(t-i)]^{1/2} \qquad (2)$$

where σ_{SL} is standard deviation of the conductance signature R_{SL} . Similarly μ_{SR} and σ_{SR} are computed from residual SCR. The feature vector also contains several measures of heart rate variability such as spectral power in the low frequency and high frequency range, mean and standard deviation of successive RR intervals, the portion of RR interval that changes more than 15 msec (pNN15) and the root mean square of successive differences of RR [23].

B. Deviations in Physiological data and Self-reporting Scores

Due to subjectivity and personal misinterpretation, deviations are introduced in the self-reporting scores leading to mismatches with the recorded physiological features. The causes for these deviations include self-description, wrong judgment, tiredness or low self-esteem as discussed earlier. Deviations can also occur in the physiological data due to individual variability. We categorized these possible deviations into three main types as shown in Figure 2.

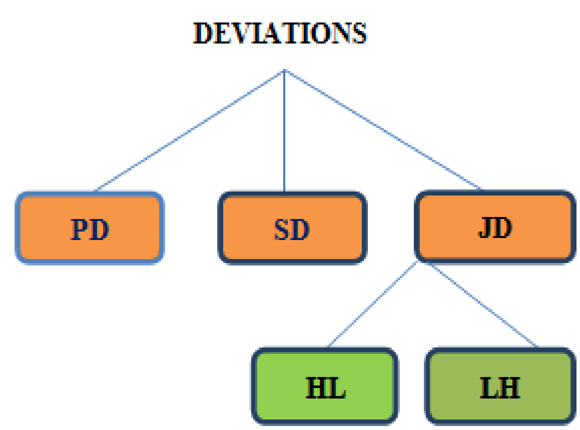

Figure 2. Tree diagram of Deviations which include Physiological Deviation (PD), Subjective Deviation (SD), Joint Deviation (JD), High score with Low parameters (HL) and Low score with High parameters (LH)

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• Physiological Deviations (PD): Here the subjects rank the activity similarly to that given by the majority of subjects (i.e. *median score range*) but their physiological parameters do not match the parameters obtained from the majority of the subjects. In this case tuning is applied to each individual feature and weighting factors are introduced to bring the parameters in the normal region.

• Subjective Deviations (SD): In this case the subject's physiological parameters are consistent with those obtained from the majority of the subjects (i.e. *median physiological range*) but the subject has ranked the activity differently from the majority of the subjects.

•Joint Deviations (JD): Both subjective scores and physiological parameters of a subject lie outside their respective median ranges of the population. Thus the subject has ranked the activity outside the median range and their physical parameters also exceed the threshold limits.

C. Correction Algorithm for Deviations

In our study, 22 subjects scored each of the 13 activities as given in Section IV in the range of 1 to 7 according to their perception of stress for these activities. To identify deviations in the data, the EDA signature was used for the following reasons. As respiration rate was controlled in our deep breathing activities and HRV is trivially related to respiration, using EDA ensured that the deviations were identified with a measure which was the least affected by respiration.

The deviations, in either score or feature, were classified using a distance metric as described by (3) and (4) for each of three parameter signatures and it was found that EDA has less deviation values than HRV and respiratory parameters. To form a representative signature for EDA, principal component analysis was performed on the four EDA features and its first principal component was extracted, which contained more than 90% variance of the features. The value of EDA principal component was also normalized between 1 and 7 to bring the response signatures in the same range as the scores.

The deviations were computed using distance metrics based on the difference of median and variables. The distance metrics for score (S) and parameter signature (F) are given by D_s and D_f such that

$$D_s = abs\ (S - M_s) \tag{3}$$

and

$$D_f = abs\ (F - M_f) \tag{4}$$

where M_s and M_f are the median of scores and median of the EDA signature, respectively.

A set of thresholds T_s (score) and T_f (feature) is defined to compute deviations (errors) in each category. If the value of a variable (score or feature) is outside its respective threshold range and it does not correspond to other variable, then that value was taken as a deviation. Hence, a careful approach was employed for selection of the threshold. The threshold is based on empirical evaluation of error and sensitivity of the system. By increasing the threshold, not only does the error decreases but the sensitivity of the system also decreases. So a tradeoff between cost of failing to detect a deviation and cost of raising false alarms is used to determine the threshold. Also the threshold range should not be either too small or too big (If threshold range is large, different class boundaries would cross each other). The comparison between distance metric and threshold resulted in four different scenarios depending on the values of F and S as given below and is presented in Figure 3 and Figure 4 showing threshold range of scores and features respectively.

- **Case 1 (True Class):** $D_s \leq T_s$ and $D_f \leq T_f$

In this case there is no deviation as both the scores and physiological features fall in the median range.

- **Case 2 (PD):** $D_s < T_s$ and $D_f > T_f$

In this case the stress scores are in the median range but the distance matrix value for the parameter signature exceeds the threshold range. To resolve this error, a weighting factor w_i is introduced to tune the feature parameters inside the normal region. An increment for each parameter is defined as,

$$\nabla f = \frac{1}{2} T_f \tag{5}$$

Then individual weighting factor is obtained as,

$$w = \frac{M_f}{f - \nabla f} \quad when\ f > M_f \tag{6a}$$

$$w = \frac{M_f}{f + \nabla f} \quad when\ f < M_f \tag{6b}$$

The overall weighting factor is computed by summation of the individual weighting factors,

$$q_f = \frac{\sum_{i=1}^{N} x_i\, w_i}{\sum_{i=1}^{N} w_i} \tag{7}$$

where f_i is the feature value and w_i is the corresponding weighting factor.

- **Case 3 (SD):** $D_s > T_s$ and $D_f < T_f$

For this error, even though the features are in the median range, the subject has reported exceptionally high or low stress scores, a judgment which does not agree with the scores with which the majority of subjects rated the activity. These deviations in scores are computed and carried in the classification model as scores are not tuned. The adjustments in score deviations are performed by subtracting score deviations from final classification error.

- **Case 4 (JD):** $D_s > T_s$ and $D_f > T_f$

Within these deviations, there are 4 possible subcases:

1. $S_i > M_s + T_s$ and $F_i > M_f + T_f$
2. $S_i < M_s - T_s$ and $F_i < M_f - T_f$

In these two cases, as both the scores and parameter signature are either greater than the maximum or less than the minimum of the median range, the anomaly in the distance

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metric is not taken as an error but due to the subject's biased interpretation of the level stress in the activity (e.g. The subject finds the relaxing activity stressful thus ranks it as stressful and his physical parameters also show that he is not relaxed. Thus as both their score and physical parameters agree so this case is not taken as a deviation).

3. $S_i > M_s - T_s$ and $F_i < M_f - T_f$

In this case, the subject's stress score is greater than the upper limit of the median range whereas the parameter signature is less than the minimum of the median range. This occurs because the subject has judged the activity to be very stressful compared to the majority of the subjects whereas the physiological features indicate that the subject is much more relaxed than the majority of the subjects.

4. $S_i < M_s - T_s$ and $F_i > M_f - T_f$

This is the opposite class; the subject's stress score is much lower than the majority whereas the parameter signature is much higher, implying that the subject has ranked the activity as not being stressful whereas the features show the opposite. As both the physiological data and stress scores have opposing anomalies in subcases 3 and 4, the deviations are computed for each subject.

In Figure 3, the stress scores and EDA response of each subject is plotted for one of the deep breathing activities. The shaded region represents the threshold range for the scores and those scores which are outside the threshold region and also do not agree with the parameter response, are marked with stars. Figure 4 is similar to Figure 3 except the threshold region now follows the EDA signature (T_s and T_f are different from each other). In Figure 5, tuning is applied to the features shown in blue using the weighting factors as discussed above. The outbound features are multiplied by the weighting factors and their range is controlled.

In Figure 6 and Figure 7, cases of deviations in scores are presented for subject 7 and subject 11, respectively. As in Figure 6, subject 7 has reported different scores for deep breathings (1 to 6) whereas majority of the subjects ranked deep breathing activity as 1. This shows that his scores are inconsistent even for a same activity. As another example, the dual task mental challenge has a median score 4 but subject 7 has ranked that activity as 1. The subject's physical parameters also do not agree with his scores and results in deviations (errors). Similarly in Figure 7, deviations for subject 11 are presented. Stars on the scores show deviations in scores for both subjects.

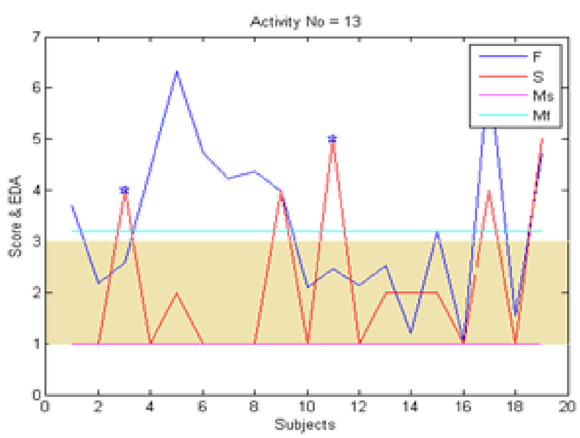

Figure 3. Stress score and EDA response with shaded portion showing threshold range for scores. Stars on scores show deviations in subjects 3 and 11

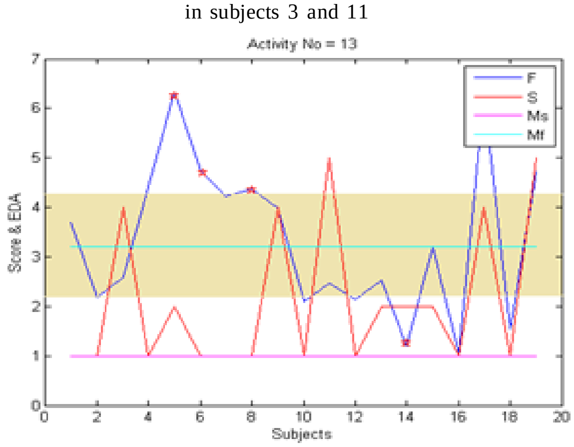

Figure 4. Stress score and EDA response with shaded portion showing threshold range for the feature. Stars on feature values for subjects 5,6,8 and 14 present deviations which are minimized by tuning of features

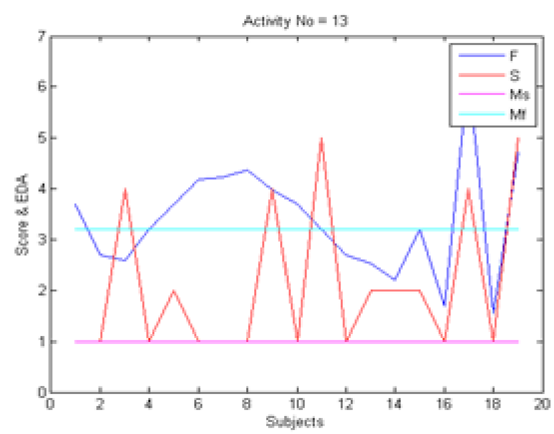

Figure 5. Weighting factors applied to the out of bound features. The features are tuned to lie within the threshold range

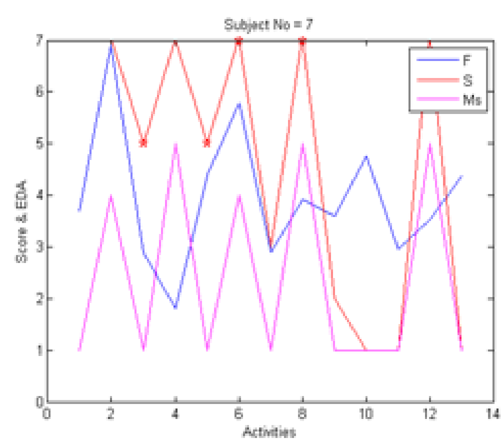

Figure 6. The feature values and scores of Subject 7 together with the median score of all the subjects for all activities as shown in Figure 1. Stars on the scores show deviations

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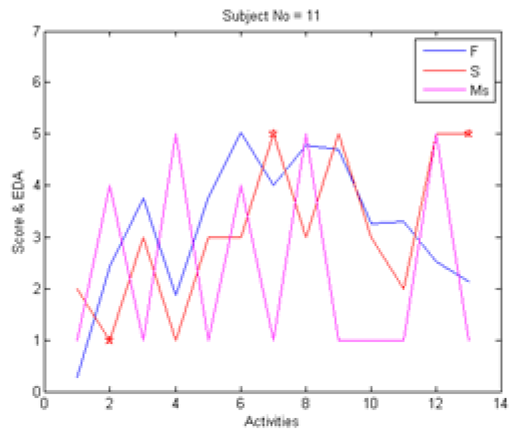

Figure 7. The feature values and scores of Subject 11 together with the median score of all the subjects

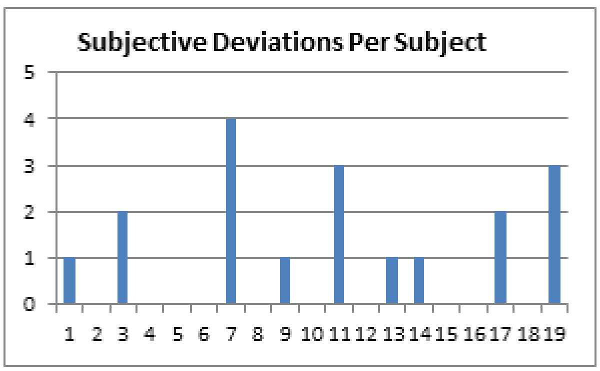

Figure 8. Deviations for each subject in EDA response

In Figure 8, total number of deviations (7%) in scores is presented. Subject 7 has highest number of deviations (4), followed by subject 11 and subject 19 (3 deviations), while subjects 17 and 3have performed only 2 deviations. The overall deviation in scores is not very large as most of the subjects (10 subjects in total) have not performed any subjective deviation.

V. Classification Model

We developed a classification model based upon a support vector machine (SVM) with the goal of predicting stress state of the subjects based on the extracted physiological features of HRV and EDA and their self-reported scores. As the relaxation activity in the protocol was deep breathing, where subjects controlled their respiratory rate, it was not used in the classifier to avoid biasing of the results. The output of the classifier was a metric which classified the mental state of the individual as being in either a relaxed class (0), low stress class (1) or high stress class (2). The input to the model was in the form of recorded physiological parameters (F_i) which are mapped or labeled to three mental states or classes (S_i) as provided by user's self-reported scores.

In our supervised model, stress scores are used for labels of the classes. Based on an initial k-means clustering analysis, we employed different number of clusters and found that compactness and separation of data is better in three clusters than four or five clusters. Hence, the score labels were divided into three classes as follows,

- Stress score 1 represents Class 1 (Relax class)
- Stress score 2, 3 & 4 denote Class 2 (Low stress class)
- Stress score 5, 6 & 7 represent Class 3 (High stress class)

Initial analysis shown in the figures 9 and 10, indicated that the separation between three classes is better in EDA than HRV features. In HRV, the high stress group is well separated but low stress and relax groups are intermixed. The heart rate variation is high during deep breathing activities but becomes low in stressful conditions thus allowing the stress group to be discriminated from the rest. In Figure 11, both HRV and EDA features are used for classification. As seen the three clusters, relax, low stress and high stress groups are well separated from each other.

A SVM was chosen as it performs a non-linear mapping from the input space to an implicit high dimensional feature space, where the nonlinear and complex distributions of the patterns in the input space are linearized so that a linear separating boundary can be applied for the classification [24]. In this case the SVM was used to map physiological parameters into self-reported scores. The SVM was based upon a radial basis function (RBF) kernel, with the best value of the cost function C and error of the cost function γ through cross validation. During cross validation, a grid search on and γ is performed. Various pairs of (, γ) values are tried and one with the best cross-validation accuracy is chosen.

One third of samples were used in the training and remaining two thirds were used in the testing. Five-fold cross validation was performed on the data by dividing training samples into five equal sets. Using cross-validation, the SVM was trained on four sets of data and fifth set was used in testing. The tuning was applied to the training set using a sequential grid search. In this procedure an iterative algorithm is applied for the incremental values of cost of optimization (C) and bandwidth γ. C is found to be 0.1 while the bandwidth is computed as 0.125 after the tuning.

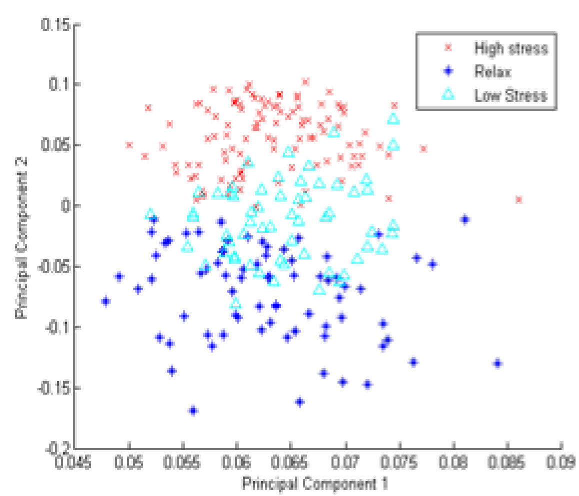

Figure 9. Scatter Plot of first two principal components of the HRV features

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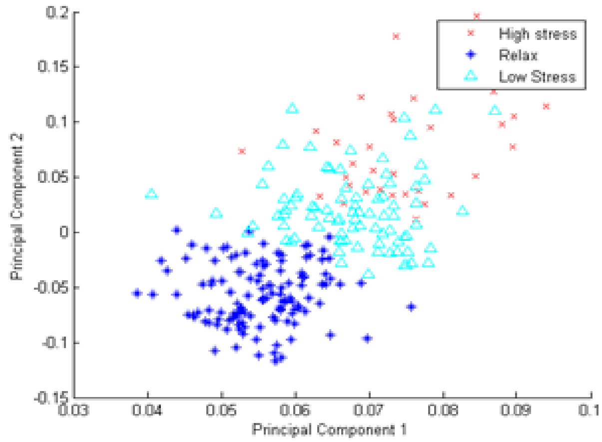

Figure 10. Scatter Plot of first two principal components of the EDA features

VI. Discussion

In our proposed adaptive model, uni-directional and bi-directional deviations in extracted physiological features and self-reported scores are first computed. Tuning was then applied to data with unidirectional physiological deviations through the use of weighting factors. The tuned data and corresponding self-reported scores are then inputted into a SVM for categorization into three stress classes. Prior to tuning data with unidirectional physiological deviations, the accuracy of the classifier was 76%. As shown in Table I, on using data tuned for unidirectional physiological deviations and subtracting unidirectional subjective deviations, the classification accuracy increases to 89.9 %, i.e. a 15 % improvement with a sensitivity and specificity of 77.7 % and 87.8 % respectively.

The deviations in the self-reported scores are not tuned. As these are perceptual judgments, tuning them on the basis of the median scores would not reflect the individual's judgment. These deviations are instead removed from the data. The average subjective scoring deviation of 8.3 % is subtracted from the 18.38% classification error reducing the overall system error to 10.1 %.

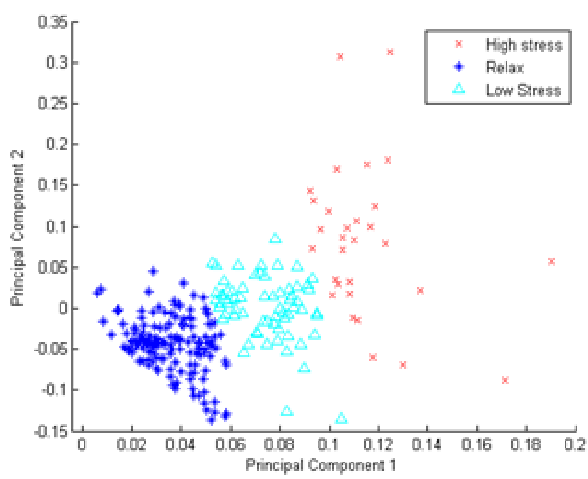

Figure 11. Scatter Plot of first two principal components of the EDA and HRV features

VII. Conclusion

We have designed an adaptive model which has a two folded effect on the system. First, it contains adjustable and tuning parameters which can adapt themselves to the individual. Secondly, it accurately classifies an individual's personal state based on physiological and psychological measures. Thus a generalized model for computation of stress is proposed which can adjust to the user's individual inner state. The initial classification error of 24 % is reduced to 10 % using our adaptive algorithm in two steps. First, tuning is performed which improves accuracy by 6 %. Secondly, subjective deviations are subtracted from the classification error to obtain 90 % classification accuracy for the adaptive model.

As stress or intensity of the reaction is in proportion to one's ability to cope with danger and degree of control over emotions, there is a need for a model which can be adjusted to levels of reactions (of stress) which vary from person to person. The proposed adapted model fulfills this requirement by using a minimally invasive wearable sensor platform for long-term ambulatory monitoring of a number of physiological parameters using self-corrections and auto adjustments. In future, the next immediate step is to perform experiments on bigger data sets collected over longer periods of time to validate the proposed adaptive model. We also plan to investigate effect of stress on gender. Finally methods to tune the self-reported scores, including stress and anxiety baseline surveys will be pursued.

Table I: Classification accuracy (%)

	Value before Tuning	***Value after Tuning***	***Value after JD Deviations***
Correct Rate	76.35	81.62	89.9
Error Rate	23.65	18.38	10.2
Sensitivity	74.66	77.78	78.78
Specificity	82.70	87.80	87.80
PositivePredictiveV alue	77.40	80.77	80.77
NegativePredictive Value	81.65	85.71	87.71

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